Energy detection using very large antenna array receivers

Oliveras Martínez, Àlex; De Carvalho, Elisabeth; Popovski, Petar; Pedersen, Gert Frølund

Published in:
48th Asilomar Conference on Signals, Systems, and Computers proceedings

DOI (link to publication from Publisher):
10.1109/ACSSC.2014.7094611

Publication date:
2014

Document Version
Accepted author manuscript, peer reviewed version

Energy detection using very large antenna array receivers

Àlex Oliveras Martínez, Elisabeth De Carvalho, Petar Popovski, Gert Frølund Pedersen
Department of Electronic Systems, Aalborg University, Denmark
email: {aom,edc,petarp,gfp}@es.aau.dk

***Abstract*—We propose the use of energy detection for single stream transmission and reception by a very large number of antennas, with primary application to millimeter wave communications. The reason for applying energy detection is low complexity, cost and power efficiency. While both energy detection and millimeter wave communications are limited to short ranges due respectively to noise sensitivity and propagation attenuation, processing by a large number of receive antennas overcomes those shortcomings to provide significant reach extension. This processing is solely based on long-term statistics of the channel and noise, making it robust to user mobility and imperfect channel knowledge.**

I. Introduction

Energy detection (ED) has been extensively employed in optical communications as it provides a low complexity and power efficient solution compared to coherent detection. More recently and for similar reasons, ED is seen as an attractive solution for short-range wireless systems at sub-millimeter waves and, lately, millimeter (mm) waves. In particular, for mm-wave communications, ED significantly simplifies the front-end of a receiver and can circumvent harmful impairments linked to the carrier phase recovery or amplifier limitations [1]. ED is a non-coherent detection. It bases symbol detection on the energy of the received signal and hence is limited to nonnegative constellations. In this work, we use non negative Pulse Amplitude Modulation (PAM) such as in mm-wave short-range wireless standards ECMA-387 and IEEE802.15.3c [2], [3]. Various aspects of PAM-ED systems have been investigated essentially for a single antenna system [4], [5], [6], [7].

Currently, the application of ED is confined to short-range communications, for which the SNR is high. The reason is that the performance of ED is limited by the presence of noise as the signal energy also embeds the noise at the receiver. Furthermore, due to the high propagation loss at mm-wave frequencies, mm-wave systems are still considered mainly suitable for short-range communications of a few meter reach.

At mm-wave frequencies, a very large number of antenna elements can be packed in a small volume (at 60GHz, the antenna size is of order 5mm). Hence, a user device or access point can easily contain an array of hundreds of antenna elements. Our solution consists of the transmission of a single data stream that is processed by a very large number of receive antennas and detected using ED. In the receive processing, the signal energy at each antenna is collected and added up. In principle, the energy of the signal of interest gets accumulated but so does the noise contribution. However, as the number of receive antennas becomes very large, the noise energy contribution becomes deterministic. If an estimate of the noise energy is available, its contribution can simply be removed. Hence, for an asymptotically large number of antennas, the performance of ED is not limited by noise like in the case of a small number of receive antennas, opening the possibility of reach extension.

Furthermore, energy accumulation from a multitude of antennas also results in an averaging of the channel energy across the array, where the impact of the channel appears through long-term statistics only. While in a conventional ED with a small number of antennas, the amplitude of each channel is needed for non-coherent detection, our solution only requires the average channel energy, a long term statistics, for which slow tracking is sufficient, hence reducing the need for training periods and making the receiver very robust to mobility. At last, resorting to the central limit theorem, the collected energy can be approximated as a Gaussian variable, significantly simplifying the computation of the detection thresholds.

Even if the transmitter possesses a massive array, only one antenna is used for transmission. Alternatively, a few antennas can be used as long as a highly directive transmission is not induced: the purpose is to guard us against CSI dependency at the transmitter or the presence of obstacles along the path of a beam. Therefore, we do not exploit transmit beamforming gain. Our hypothesis is that this can be compensated for by the very large number of antennas at the receiver which is capable of granting the desired reach extension by itself. Transmit beamforming gain is sacrificed so that extreme robustness to user movement, noise and channel knowledge can be gained and importantly low cost thanks to the use of ED.

In the recent development of massive MIMO [8], the presence of a massive number of antennas at the base station participates to an averaging of the fading and noise. However, this requires a coherent processing that is successful if the channel state information (CSI) is known with high reliability. The processing that is proposed in this paper can be extended to the uplink of a massive MIMO cellular system at lower frequency ($<$6GHz) as described in [8]. The target is not high throughput but rather ultra-reliable single user transmission.

In summary, the use of ED combined with a large antenna array processing at the receiver allows for low cost and power efficient solution with simplified front-end particularly well-suited for mm-wave communications. Because it relies on long-term statistics of the channel and noise, it represents an ultra-reliable solution robust to user mobility and noise. After the submission of this work, we came across [9] (and follow-up work) where the principle of energy detection based on statistics is also applied. However, the ensuing proposed approaches are different from the ones presented in this paper.

The paper is organized as follows. After presenting the system model for ED in section II, we describe the conventional ED procedure in section III, as performed in the case of a small number of antennas. In section IV, we present our solution and the performance results are given in section VI. We use $(.)^*$, $(.)^T$ $(.)^H$, $E(.)$ to denote complex conjugation, transpose, transpose Hermitian and expected value operations.

II. System Model

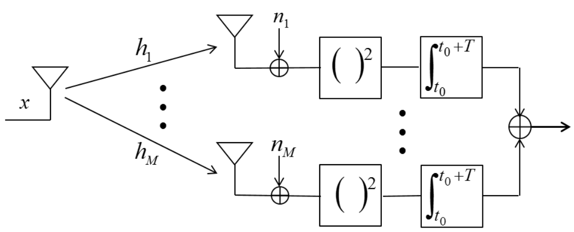

Fig. 1. Energy collector: energy at each receive antenna is added up.

We consider a system where one data stream is transmitted from one antenna and received by a very large number M of antennas: see figure 1. The system operates in time-division duplexing. We assume that each device, which could be an access point or a user equipment, contains a very large antenna array: in transmit mode, the device uses a single antenna, while, in receive mode, it uses the whole set of antennas.

As commonly assumed in ED-PAM [5], we consider PAM with guard interval where the guard interval serves to avoid Inter-Symbol Interference (ISI). Importantly, ED-PAM with a very large number of receive antennas provides tools to combat ISI. Further details are given in section VII. The transmitted symbol is generically denoted as x:

$$x \in \{0, \sqrt{\epsilon_1}, \sqrt{\epsilon_2}, \ldots, \sqrt{\epsilon_{P-1}}\} \tag{1}$$

where $\sqrt{\epsilon_p} = (p-1)\sqrt{\mathcal{E}}$: $\sqrt{\mathcal{E}}$ is determined such that the average energy of the constellation is normalized.

We make the hypothesis of a rich scattering environment, so that the channel coefficient $\tilde{h}_i(t)$ from the transmit antenna to the receive antenna i at time t is modeled as a zero-mean complex circularly symmetric Gaussian random variable. The channels to different receive antennas are uncorrelated. The channel process is assumed to be stationary and a channel coefficient has energy denoted as $E|\tilde{h}_i|^2 = \sigma_h^2$. The average transmit power is set to be equal to 1.

With transmission of symbol x, and adopting compact notations with complex quantities, the received signal at antenna $i \in [1 \ldots M]$ and time t is written as:

$$y_i(t) = \tilde{h}_i(t)x + \tilde{n}_i(t). \tag{2}$$

$\tilde{n}_i(t)$ is a zero-mean circularly symmetric Gaussian variable with variance σ_n^2. The noise represents a thermal noise at the receiver or interference. It is independent across receive antennas. At each antenna, the receive signal is filtered, squared and integrated. A description of an equivalent model for the received signal can be found in e.g. [5]. Assuming that the available degrees of freedom are brought by the multiple antennas, the signal can be written as:

$$\mathbf{Y} = \frac{1}{M}\sum_{i=1}^{M} |h_i x + n_i|^2 . \tag{3}$$

h_i and n_i are the equivalent channel and noise term after integration. Division by M is introduced for convenience. We denote $\mathbf{h}$ as a vector grouping all the channel coefficients: $\mathbf{h} = [h_1\ h_2 \ldots h_M]^T$.

III. Maximum Likelihood Detection

Maximum likelihood detection is applied to test the hypothesis $\mathcal{H}_p$ that the symbol $x = \sqrt{\epsilon_p}$ was transmitted, based on the observation $\mathbf{Y}$. $\mathcal{H}_p$ is validated if:

$$f(\mathbf{Y}|\mathcal{H}_p) > f(\mathbf{Y}|\mathcal{H}_{p'}), \quad \forall p' \neq p \tag{4}$$

where $f(\mathbf{Y}|\mathcal{H}_p)$ is the conditional probability density function (pdf) of $\mathbf{Y}$. Equation (4) is used to find the detection thresholds between 2 neighboring constellation points that we denote as Δ_p, $p = 0, \ldots P-2$: ϵ_p is detected if $\mathbf{Y} < \Delta_p$, otherwise ϵ_{p+1} is detected.

A. Coherent detection

It is instructive to examine the fundamental differences between coherent and non-coherent detection (ED) to understand the main challenges of ED. In coherent detection, each channel coefficient h_i is known at the receiver. The optimal receiver consists of maximum ratio combining where each of the M antenna outputs is multiplied by h_i^* and combined as:

$$\mathbf{Y}_c = \sum_{i=1}^{M} \tilde{h}_i^* y_i = \sum_{i=1}^{M} \tilde{h}_i^* \tilde{h}_i x + \sum_{i=1}^{M} h_i^* \tilde{n}_i = \|\tilde{\mathbf{h}}\|^2 x + \sum_{i=1}^{M} \tilde{h}_i^* \tilde{n}_i. \tag{5}$$

Conditioned on the transmission of x, $\mathbf{Y}_c$ follows a Gaussian distribution with mean $\|\tilde{\mathbf{h}}\|^2 x$. Two observations can be made. First, as the Gaussian distribution is symmetric around $\|\tilde{\mathbf{h}}\|^2 x$, the decision threshold to detect ϵ_p or ϵ_{p+1} is simply equal to $\|\tilde{\mathbf{h}}\|^2(\epsilon_p + \epsilon_{p+1})/2$, or $(\epsilon_p + \epsilon_{p+1})/2$ if detection is based on $\mathbf{Y}_c/\|\tilde{\mathbf{h}}\|^2$. Second, the output combining in MRC results in an averaging of the noise terms $\tilde{n}_i$: as the number of receive antennas grows, the noise term in equation (5) gets suppressed.

B. Non-coherent detection

In non-coherent detection, only the amplitude $|h_i|$ of the channel coefficient is known at the receiver. ML detection is based on $\mathbf{Y}$ in equation (3) which follows a non-central chi-square distribution with $2M$ degrees of freedom. The conditional pdf of $\mathbf{Y}$ is rewritten as $f(\mathbf{Y}|\mathbb{E}[\mathbf{h}], \epsilon_p)$ to clearly mark the dependencies. $\mathbb{E}[\mathbf{h}]$ is the instantaneous channel energy at a given time instant:

$$\mathbb{E}[\mathbf{h}] = \frac{1}{M}\sum_{i=1}^{M} |h_i|^2 = \frac{1}{M}\|\mathbf{h}\|^2 \tag{6}$$

$$f_{\mathbf{Y}}(\mathbf{Y}|\mathbb{E}[\mathbf{h}], \epsilon_p) = \begin{cases} \frac{M}{2\sigma_n^2} e^{-\frac{M}{2\sigma_n^2}\mathbf{Y}} \left(\frac{M}{2\sigma_n^2}\mathbf{Y}\right)^{M-1} \frac{1}{(M-1)!}, & \text{if } m = 0 \\ \frac{M}{2\sigma_n^2} e^{-\frac{M}{2\sigma_n^2}(\mathbf{Y}+\mathbb{E}[\mathbf{h}]\epsilon_p)} \left(\frac{\mathbf{Y}}{\mathbb{E}[\mathbf{h}]\epsilon_p}\right)^{\frac{M-1}{2}} I_{M-1}\left(\frac{M}{2\sigma_n^2}\sqrt{\mathbf{Y}\mathbb{E}[\mathbf{h}]\epsilon_p}\right), & \text{if } m > 0 \end{cases} \tag{7}$$

$I_\nu(z)$ is the modified Bessel of the first kind.

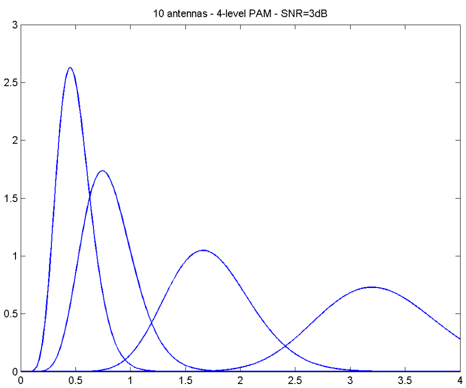

Fig. 2. Pdfs of the received energy in equation (3) for a given channel realization with 10 receive antennas and a 4-level non negative PAM.

Figure 2 depicts the pdfs for a 4-level non negative PAM and 10 receive antennas where it is clearly observed that the pdfs are not symmetric. Similar to coherent detection, two observations can be made. First, in general, the detection thresholds do not have a closed form expression and require determining the intersection points of neighboring pdf curves via numerical methods for each channel realization. Second, from equation (3), when collecting energy from all antennas, noise energy is also collected. Hence, at first sight, ED does not provide noise suppression.

IV. Energy Detection for Asymptotically Large Number of Antennas

The expression of signal $\mathbf{Y}$ with transmission of $\sqrt{\epsilon_p}$ is developed as:

$$\mathbf{Y} = \frac{1}{M}\sum_{i=1}^{M}\left|h_i\sqrt{\epsilon_p} + n_i\right|^2 = \tag{8}$$

$$\underbrace{\frac{1}{M}\sum_{i=1}^{M}\left|h_i\right|^2 \epsilon_p}_{\mathbb{E}[\mathbf{h}] \xrightarrow{M\to\infty} \sigma_h^2} + \underbrace{\frac{1}{M}\sum_{i=1}^{M}\left|n_i\right|^2}_{\xrightarrow{M\to\infty} \sigma_n^2} + \underbrace{2\frac{1}{M}\sum_{i=1}^{M} Re(h_i n_i^*)\epsilon_p}_{\xrightarrow{M\to\infty} 0} \tag{9}$$

A receive processing based on an asymptotically large number of antennas relies on the asymptotic behavior of the terms in (9) which tend to their expected value as M tends to ∞: a) the first term in the sum tends asymptotically to the channel energy σ_h^2, b) the second term tends to σ_n^2, c) the third term involving cross terms tends to 0.

The observations drawn from (9) suggest that the energy detection can be carried out based solely on second-order statistics of the channel and the noise:

- As the noise contribution in the received signal becomes deterministic, in principle, its contribution can be removed from (9) provided that the noise variance σ_n^2 has been estimated. Therefore, asymptotically, such a detection procedure does not suffer from degradations due to the accumulation of noise in the energy addition in (3).
- While the amplitude of each channel coefficient is necessary to form the term $\frac{1}{M}\sum_{k=1}^{M}|h_k|^2$ (used by ED for a small number of antennas), this term can be substituted by a channel energy estimate when M becomes large.

Furthermore, according to the central limit theorem, the received signal $\mathbf{Y}$ in (8) can be approximated as a Gaussian random variable. This approximation leads to closed-form expressions of the detection thresholds which is a notable advantage over ED with small antennas for which a numerical method should be employed to determine the crossing points between non-central chi-square pfds.

Based on the key observations described above, we propose 3 ED methods that are described below. We assume that the noise energy is constant over time. Its estimation is performed over a very large number of periods (idle mode) and will be in general much better than the channel energy estimation. As a consequence and to simplify, we assume that the noise variance is perfectly known.

A. **Approach 1**: *ED based on Gaussian approximation*

For large M, $\mathbf{Y}$ in (8) is approximated as a non-centered Gaussian random variable, i.e. $\mathbf{Y} \sim \mathcal{CN}(m_Y, \sigma_Y^2)$. The mean m_Y and variance σ_Y^2 are obtained using the expressions of the mean and variance of a non-central chi-squared random variable:

$$\mu_Y(\mathbb{E}[\mathbf{h}], \epsilon_p) = \mu_{Y,p} = \mathbb{E}[\mathbf{h}]\epsilon_p + \sigma_n^2 \tag{10}$$

$$\sigma_Y^2(\mathbb{E}[\mathbf{h}], \epsilon_p) = \sigma_{Y,p}^2 = \frac{\sigma_n^2}{M}\left(2\mathbb{E}[\mathbf{h}]\epsilon_p + \sigma_n^2\right). \tag{11}$$

The non-central chi-square pdf in (7) is approximated by a conditional non-centered Gaussian pdf denoted as:

$$f(\mathbf{Y}|\mathbb{E}[\mathbf{h}], \epsilon_p) \approx g(\mathbf{Y}|\mathbb{E}[\mathbf{h}], \epsilon_p). \tag{12}$$

The detection thresholds are determined as the intersection points between the different conditional pdfs. The detection threshold Δ_p is the positive root of the second-order polynomial equation:

$$\left[1/\sigma_{Y,p}^2 - 1/\sigma_{Y,p+1}^2\right]x^2 - 2\left[\mu_{Y,p}/\sigma_{Y,p}^2 - \mu_{Y,p+1}/\sigma_{Y,p+1}^2\right]x + \left[\mu_{Y,p}^2/\sigma_{Y,p}^2 - \mu_{Y,p+1}^2/\sigma_{Y,p+1}^2\right] - \log\left[\sigma_{Y,p+1}^2/\sigma_{Y,p}^2\right] = 0. \tag{13}$$

B. **Approach 2**: *ED based on Gaussian approximation and channel energy estimation*

Next, we assume that we have an estimate of the channel average energy denoted as $\widehat{\mathbb{E}}$ (see section V). ML detection is performed now based on $g(\mathbf{Y}|\widehat{\mathbb{E}}, \epsilon_p)$. The advantage consists in determining the detection thresholds only when the channel energy varies significantly, instead of determining them for each channel realization. In approach 2, the following approximation is made:

$$g(\mathbf{Y}|\mathbb{E}[\mathbf{h}], \epsilon_p) \approx g(\mathbf{Y}|\widehat{\mathbb{E}}, \epsilon_p). \tag{14}$$

The detection thresholds are determined based on (13) where $\mu_{Y,p}$ and $\sigma_{Y,p+1}^2$ are computed based on $\widehat{\mathbb{E}}$.

C. **Approach 3** *ED based on a priori knowledge of channel distribution*

We assume now that the channel is a random variable, and, more specifically, as mentioned in section II, an i.i.d. Gaussian random variable. Let $\widehat{\mathbb{E}}$ be the current estimate of the channel energy. Looking at equation (8), $\mathbf{Y}$ would follow a centered chi-squared distribution with distribution:

$$b(\mathbf{Y}|\widehat{\mathbb{E}}, \epsilon_p) = \frac{M}{2\sigma_n^2} e^{-\frac{M}{2(\widehat{\mathbb{E}}\,\epsilon_p+\sigma_n^2)}\mathbf{Y}} \left(\frac{M}{2(\widehat{\mathbb{E}}\,\epsilon_p+\sigma_n^2)}\mathbf{Y}\right)^{M-1} \frac{1}{(M-1)!}. \quad (15)$$

The detection thresholds are determined based on $b(\mathbf{Y}|\widehat{\mathbb{E}}, \epsilon_p)$. Remarkably, the detection thresholds have a closed-form expression that only depends on the SNR, defined as $\rho = \widehat{\mathbb{E}}/\sigma_n^2$ (and not the number of antennas):

$$\Delta_p = \log\left[\frac{(\rho\epsilon_{p+1}+1)}{(\rho\epsilon_p+1)}\right] \frac{(\rho\epsilon_{p+1}+1)(\rho\epsilon_p+1)}{\rho(\epsilon_{p+1}-\epsilon_p)}. \quad (16)$$

Although this approach relies on a specific distribution of the channel, a more robust method can be devised. Based on the Gaussian approximation and provided that the first and second-order statistics of Y (w.r.t. channel and noise) can be estimated, appropriate thresholds can be determined according to (13).

D. *Illustrative example*

We show in figure 3 the pdfs and the detection thresholds for a 4 level-PAM and 200 receive antennas. The curves are: a) approach 1: the non-central chi-square distribution in (7), the optimal thresholds and the thresholds obtained via (13), b) approach 2: the non-central chi-square distribution in (7) where $\mathbb{E}[\mathbf{h}]$ is replaced by $\widehat{\mathbb{E}} = \sigma_h^2$ and the thresholds obtained via (13), c) approach 3: the central chi-square distribution in (15) and the thresholds obtained via (16). First, we observe that

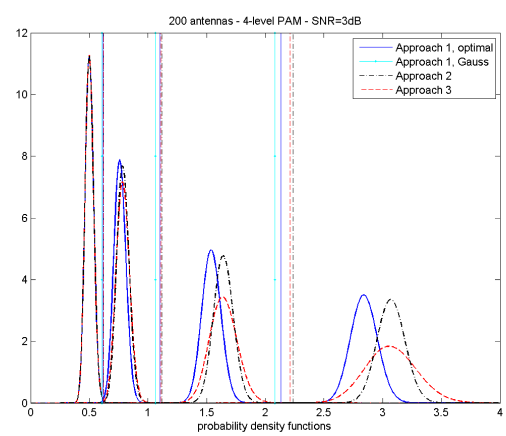

Fig. 3. Pdfs of the received energy in (3) for a given channel realization, 200 receive antennas and a 4-level non negative PAM. Vertical lines indicate the thresholds.

the variance is significantly reduced compared to the case of 10 antennas shown in figure 2, illustrating the gain brought by the presence of many antennas in diminishing the uncertainty in the random processes involved. Furthermore, for the selected channel realization, the pdf in case a) is well approximated by the pdf in case b) for lower PAM levels. However, for higher PAM levels, this approximation becomes more critical, as the estimation error between $\mathbb{E}[\mathbf{h}]$ and its approximation $\widehat{\mathbb{E}} = \sigma_h^2$ gets multiplied by a large PAM level value. This results in detection thresholds that are dissimilar in case a), case b), and case c). In this example, we notice that the thresholds in approach 3 are closer to the optimal thresholds.

V. Channel energy estimation

Channel energy estimation should be taken care of properly, especially at high SNR where estimation errors are responsible for an error floor. We consider two estimation strategies exhibiting very distinct performance properties: one fitted to slowly varying channels and one fitted to fast varying channels.

A. *Slowly varying channels*

Channel energy is estimated during a training phase and we assume that the channel remains unchanged during the training phase and the data transmission phase. A number of K training symbols equal to 1 are transmitted. We want an estimate of $\mathbb{E}[\mathbf{h}]$ for the specific value of the channel, assumed constant, during the time period considered. Denoting $\mathbf{Y}(k) = \frac{1}{M}\sum_{i=1}^{M}|h_i+n_i(k)|^2$ as the received signal energy collected at transmission time slot k, channel energy is estimated as:

$$\widehat{\mathbb{E}}[\mathbf{h}] = \frac{1}{K}\sum_{k=1}^{K}\mathbf{Y}(k) - \sigma_n^2. \quad (17)$$

In the case of very low SNR and low number of receive antennas, the quantity in equation (17) might be negative, in which case σ_n^2 is not subtracted. It can be shown that the estimation error $E(\mathbf{h}) - \widehat{E}(\mathbf{h})$ is of order $O(\frac{\sigma_n}{\sqrt{KM}})$, which is negligible compared to the noise term in (3).

B. *Fast varying channels*

We assume that the value of the channel changes independently between the training phase and the data transmission phase. The channel energy estimation as described in equation (17) is not as relevant when the channel changes its value. In that case, it is of interest to strengthen further the channel energy estimation by accumulating estimates as in (17) over multiple time slots (or training periods) and even data transmission phases (requiring an averaging over the transmitted symbol energy). Denoting as K' the number of transmission slots involved in the estimation, the estimation error $\mathbb{E}[\mathbf{h}] - \widehat{\mathbb{E}}$ is of order $O(\frac{\sigma_h}{\sqrt{K'M}})$ at high SNR. Unlike the slow varying channel case, the estimation error becomes non negligible compared to the noise term in (3) at very high SNR, creating an error floor.

VI. Simulations

We consider 2 extreme cases of channel variation: in figure 4, the channel takes independent values from the training to the data phase (block fading) and in figure 5, the channel remains time-invariant. To simplify, we assume that the statistics of the channel are perfectly estimated, i.e. $\widehat{\mathbb{E}} = \sigma_h^2$. Likewise, in the time-invariant case, $\mathbb{E}[\mathbf{h}]$ is perfectly estimated. The impact of the estimation errors is left for further work. The table below summaries the approaches considered in this section.

	Block-Fading $\mathbf{h}_{\text{TS}}$, $\mathbf{h}_{\text{Data}}$ independent	**Time-invariant** $\mathbf{h} = \mathbf{h}_{\text{TS}} = \mathbf{h}_{\text{Data}}$
Approach 1	$\widehat{\mathbb{E}} = \mathbb{E}[\mathbf{h}_{\text{TS}}]$ Thresholds (13)	$\times$ $\times$
Approach 2	$\widehat{\mathbb{E}} = \sigma_h^2$ Thresholds (13)	$\widehat{\mathbb{E}} = \mathbb{E}[\mathbf{h}_{\text{TS}}]$ Thresholds (13)
Approach 3 (Bayesian)	$\widehat{\mathbb{E}} = \sigma_h^2$ Thresholds (16)	$\widehat{\mathbb{E}} = \mathbb{E}[\mathbf{h}_{\text{TS}}]$ Thresholds (16)

TABLE I
SUMMARY OF THE SIMULATED CASES

The symbol error rate (SER) for uncoded PAM is computed semi-analytically as follows. We denote $F(\Delta|\mathbb{E}[\mathbf{h}], \epsilon_p)$ as the cumulative density function conditioned on the channel realization and transmission of ϵ_p:

$$P_e(\mathbb{E}[\mathbf{h}], \epsilon_p) = \begin{cases} 1 - F(\Delta_p|\mathbb{E}[\mathbf{h}], \epsilon_p), & \text{if } p = 0 \\ F(\Delta_{p-1}|\mathbb{E}[\mathbf{h}], \epsilon_p) + 1 - F(\Delta_p|\mathbb{E}[\mathbf{h}], \epsilon_p), & \text{if } 0 < p < P-1 \\ F(\Delta_{p-1}|\mathbb{E}[\mathbf{h}], \epsilon_p), & \text{if } p = P-1 \end{cases} \tag{18}$$

The probability of error is obtained by averaging $P_e(\mathbb{E}[\mathbf{h}], \epsilon_p)$ over Monte-Carlo runs of the channel. The resulting SER curves are shown as a function of the number of receive antennas for a growing SNR $\rho = \sigma_h^2/\sigma_n^2$ of 0, 3, 6, 9, 12dB.

For a block fading channel, detection remains robust at lower SNR (0dB, 3dB) compared to the case of a time-invariant channel but degrades at higher SNR (6dB and larger). All methods encounter an error floor as described in section V-B. Approach 1 performs poorly at higher SNR, while the best performance is given by Bayesian ED. For a time-invariant channel, both approaches behave similarly.

As a conclusion and as expected, performance gets better as the number of antennas grows. For time-invariant channels, performance is very robust. For time-variant channels, the SER meets an error floor which can be decreased as the number of antennas grows.

VII. CONCLUSION AND FUTURE WORK

This paper has set the ground for ED at mm-wave using a very large number of antennas at the receiver. ED can insure ultra-reliable communications that are robust to user mobility and interference. Future works include the incorporation of more sophisticated channel models accounting for inter-link correlations. Furthermore, we have investigated the case of PAM with guard interval, preventing from ISI as suppression of ISI after ED is difficult to achieve. For ISI channels, our asymptotic treatment enables suppression of ISI and relaxation of the guard interval requirement: indeed, asymptotically, the cross-terms between multi-path components can be eliminated, letting appear a conventional ISI channel that can be treated by an equalizer. The evaluation of such a scheme is left for future work.

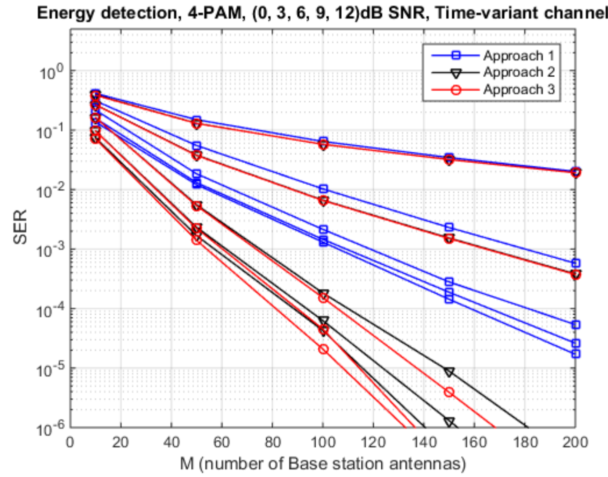

Fig. 4. Time-variant channel: SER vs number of antennas

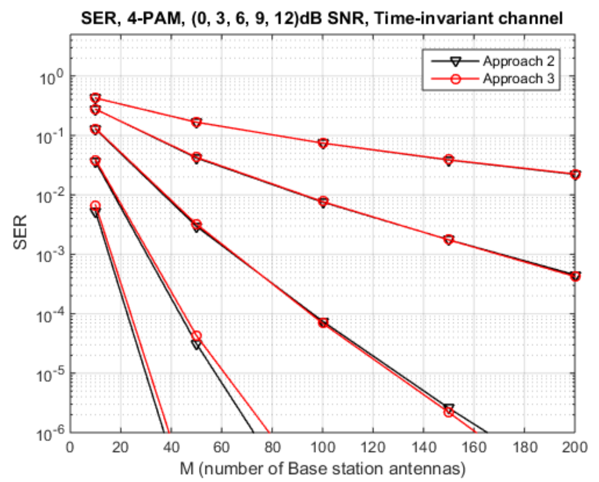

Fig. 5. Time-invariant channel: SER vs number of antennas

REFERENCES

[1] R. Daniels and R. Heath, "60 GHz wireless communications: emerging requirements and design recommendations," *IEEE Vehicular Technology Magazine*, vol. 2, no. 3, pp. 41–50, Sept 2007.

[2] S.-K. Yong, P. Xia, and A. Valdes-Garci, *60GHz Technology for Gbps WLAN and WPAN: From Theory to Practice*. Wiley, 2010.

[3] T. Baykas, C.-S. Sum, Z. Lan, J. Wang, M. Rahman, H. Harada, and S. Kato, "IEEE 802.15.3c: the first IEEE wireless standard for data rates over 1 Gb/s," *IEEE Communications Magazine*, vol. 49, no. 7, 2011.

[4] S. Paquelet and L.-M. Aubert, "An energy adaptive demodulation for high data rates with impulse radio," in *IEEE Radio and Wireless Conference*, Sept 2004, pp. 323–326.

[5] A. Anttonen, A. Mammela, and A. Kotelba, "Error probability of energy detected multilevel PAM signals in lognormal multipath fading channels," in *IEEE International Conference on communications*, 2009.

[6] R. Moorfeld and A. Finger, "Multilevel PAM with optimal amplitudes for non-coherent energy detection," in *International Conference on Wireless Communications Signal Processing*, Nov 2009.

[7] F. Wang, Z. Tian, and B. Sadler, "Weighted energy detection for non-coherent ultra-wideband receiver design," *IEEE Transactions on Wireless Communications*, vol. 10, no. 2, pp. 710–720, February 2011.

[8] T. Marzetta, "Noncooperative cellular wireless with unlimited numbers of base station antennas," *IEEE Transactions on Wireless Communications*, vol. 9, no. 11, pp. 3590–3600, November 2010.

[9] M. Chowdhury, A. Manolakos, and A. Goldsmith, "Design and performance of noncoherent massive SIMO systems," in *2014 48th Annual Conference on Information Sciences and Systems (CISS)*, March 2014.